

# Joint Power and Bandwidth Allocation for 3D Video SoftCast

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## ABSTRACT

Unlike digital video transmission systems, SoftCast avoids the cliff effect and achieves a linear video quality transition that is commensurate with the wireless channel conditions. When SoftCast is applied to three-Dimension Video (3DV) transmission, resource allocation issues arise: 1) allocating the limited power budget to texture and depth to achieve the optimal overall quality. 2) distributing the suitable number of texture and depth chunks to adapt to bandwidth constraints. This work aims to efficiently solve the optimal joint power and bandwidth allocation problem. First, a power-distortion optimization problem is formulated to calculate the optimal Power Allocation Ratio (PAR) between texture and depth, then mapped to an unconstrained problem and solved using the Lagrangian multiplier. Finally, based on the closed-form of the optimal solution, an iterative algorithm is proposed to choose the suitable number of texture/depth chunks for a given bandwidth constraint. The proposed method achieves better performance than its counterpart default fixed-ratio power allocation between texture/depth. Further, we observe a graceful video quality transition with the improvement of channel conditions under bandwidth constraints.

## CCS CONCEPTS

• Information systems → Multimedia streaming.

## KEYWORDS

power allocation, 3D-DCT, bandwidth allocation, distortion minimization

### ACM Reference Format:

SAQR KHALIL SAEED THABET, EMMANUEL OSEI-MENSAH, LEI LUO, and CE ZHU. 2022. Joint Power and Bandwidth Allocation for 3D Video SoftCast. In *2022 6th International Conference on Digital Signal Processing*

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ICDSP 2022, February 25–27, 2022, Chengdu, China

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ACM ISBN 978-1-4503-9580-9/22/02...\$15.00

<https://doi.org/10.1145/3529570.3529600>

(ICDSP) (ICDSP 2022), February 25–27, 2022, Chengdu, China. ACM, New York, NY, USA, 6 pages. <https://doi.org/10.1145/3529570.3529600>

## 1 INTRODUCTION

The 3DV has become a favorable choice for many consumers in several application domains such as industry, healthcare, education, and home entertainment. The Multiview video plus depth (MVD) [6] technique has been adopted to observe 3D video content efficiently. Meanwhile, with the advances in wireless communication (e.i., 5G and LTE) and the existence of virtual reality (VR), 3D-enabled laptops, and naked-eye 3D mobile devices, the 3D video-based applications on mobile devices are expected to attract consumers' attention. Nevertheless, some technical challenges exist. First, video data grows proportionally to the number of cameras and frame depth, which brings grave complications to the resource-constrained mobile terminals. Second, the wireless channel unreliability poses a higher requirement for 3D video transmission than traditional 2D video. Hence, any proposed efficient wireless transmission method must address these specific issues.

For Multiview video plus depth (MVD), several closely spaced cameras record texture and depth map frames of the same 3D scene. After selecting the preferred virtual viewpoint, the transmitter encodes and sends the texture and depth data of two or more neighboring viewpoints close to the selected virtual viewpoint. The demanded virtual viewpoint at the receiver is synthesized from the decoded texture video and depth map frames [11] via a technique named depth image-based rendering (DIBR).

For conventional video transmission over wireless networks, the digital video compression part of the system operates separately from the transmission part [7] to reduce the data size and ensure reliable transmission over the wireless channels. Nonetheless, the conventional scheme is unsuitable for wireless communication where the channel condition could fluctuate drastically. The encoded data is highly vulnerable to channel capacity mismatch or irreversible transmission error. When the transmission channel quality falls under a certain threshold and bit errors occur during communication—the texture and depth decoding collapse, affecting the virtual viewpoint rendering. Consequently, the reconstructed video quality of the virtual viewpoint degrades abruptly. Even when the transmission channel improves, the reconstruction quality will not improve. This phenomenon is known as the cliff effect.

An uncoded video transmission technique, SoftCast, has been proposed [4], where the joint source and channel coding is utilized. The video frames skip quantization and entropy coding and are directly transformed by 3D-DCT. Then analog modulation scales DCT coefficients linearly to minimize end-to-end distortion. Since all the associated operations are linear, the channel noise is directly mapped to the reconstruction distortion. The received video quality is commensurate with the wireless channel SNR without any cliff effects. Pseudo-analog systems implement power allocation for power redistribution among coefficients as every group of neighboring coefficients are packed in a chunk, and in case of an inadequate bandwidth, chunks with the lowest power are discarded. Several works discussed various methods to enhance the uncoded video transmission performance. Fan et al. [2] used Compensated Temporal Filter (MCTF) instead of 3D-DCT for better temporal and spatial redundancy removal. Cui et al. [1] proposed achieving the optimal transmission power by adapting chunk division. Some studies promote merging digital transmission alongside analog transmission to form a Hybrid digital-analog framework to get the most of both concepts, balancing between efficient coding and robust adaptation.

However, almost all schemes suggested apply to 2D images/videos, and a few studies considered MVD transmission. Fujikhashi et al. [3] adopted 5D-DCT to exploit the inter-view and texture-depth correlations. In [9], Yang et al. focused more on depth maps uncoded wireless transmission, considering view-synthesis distortion and scaling chunks formed by rearranging inter-block DCT coefficients to improve power allocation efficiency. Zhang et al. [10] proposed resource control algorithms based on 5D-DCT decorrelation to resolve two problems: achieve the minimum distortion under a resource constraint and minimize resource usage for a target distortion. Luo et al. [5] considered the power-distortion optimization problem with respect to the view synthesis distortion to achieve optimal overall reconstruction quality at the reference and virtual views. A closed-form of joint texture/depth power allocation is proposed to solve that optimization problem. The estimated joint power allocation helped to avoid causing geometric distortion on virtual views or additional distortions on reference views by balancing the power assigned to texture and depth maps.

Nonetheless, it did not discuss how to allow uncoded 3DV transmission to accommodate the limited bandwidth allocated. Unlike 2DV uncoded transmission systems, which resort to discarding chunks with the smallest variation to meet the constrained resource requirement without significantly degrading quality, 3DV uncoded transmission systems can face some complications. Due to the synthesis distortion involvement, the source data that can be discarded from both texture and depth frames must not significantly degrade virtual view quality and not just the reference view quality. Hence, this work aims to jointly allocate power between texture and depth to achieve optimal video quality under limited bandwidth. We propose a bandwidth allocation algorithm to enhance the uncoded 3DV transmission capability to adapt to the resource constraint environment. Our proposed method shows an adaptable performance over a wide wireless channel range.

## 2 JOINT POWER AND BANDWIDTH ALLOCATION ALGORITHM

As presented in [5], the calculated 3D video overall quality in response to using different *PAR* in scaling texture/depth shows that different *PAR* settings induce different overall quality. Moreover, as long as the optimal *PAR* varies for different sequences, the efficiency of the power allocation that decides the quality depends on the video content. Hence, we utilize a power-distortion model to obtain the optimal joint texture/depth *PAR* based on the power and quality relationship. Then we extend this model to address the bandwidth and quality relationship where an iterative algorithm is designed to search for the optimal combination of texture/depth chunks suitable for a given bandwidth constraint.

### 2.1 Problem Formulation

Given  $M$  number of reference viewpoints are transmitted in a 3D video SoftCast transmission, the total power  $P_{total}$  required to transmit the reference viewpoints textures and depths is:

$$P_{total} = \sum_{i=1}^M (P_{t,i} + P_{d,i}) \quad (1)$$

where  $P_{t,i}$  and  $P_{d,i}$  are the transmission powers for texture and depth of  $i^{th}$  reference viewpoint, respectively. If  $L$  number of virtual viewpoints are to be synthesized at the receiver, then the total distortion of all possible viewpoints  $D_{total}$  is:

$$D_{total} = \sum_{i=1}^M D_{t,i} + \sum_{i=1}^L D_{v,i} \quad (2)$$

where  $D_{t,i}$  and  $D_{v,i}$  are the distortions of  $i^{th}$  reference view and the  $i^{th}$  virtual view, respectively.  $D_{t,i}$  is only included, not  $D_{d,i}$ , because texture videos usually need to maintain higher quality to be compatible with 2-D display [8]. To simplify building the power-distortion model, we presume the power utilized for each reference view is the same.  $P_t$  is the same for all  $P_{t,i}$  and  $P_d$  is also the same for all  $P_{d,i}$ . Thus, the problem of joint power allocation that optimally designates the texture/depth *PAR* to minimize the total distortion of all viewpoints is formulated as:

$$D_{total}(P_t, P_d) = \arg \min_{(P_t, P_d)} \sum_{i=1}^M D_{t,i}(P_t) + \sum_{i=1}^L D_{v,i}(P_t, P_d) \quad (3)$$

s.t.  $M(P_t, P_d) < P_{total}$

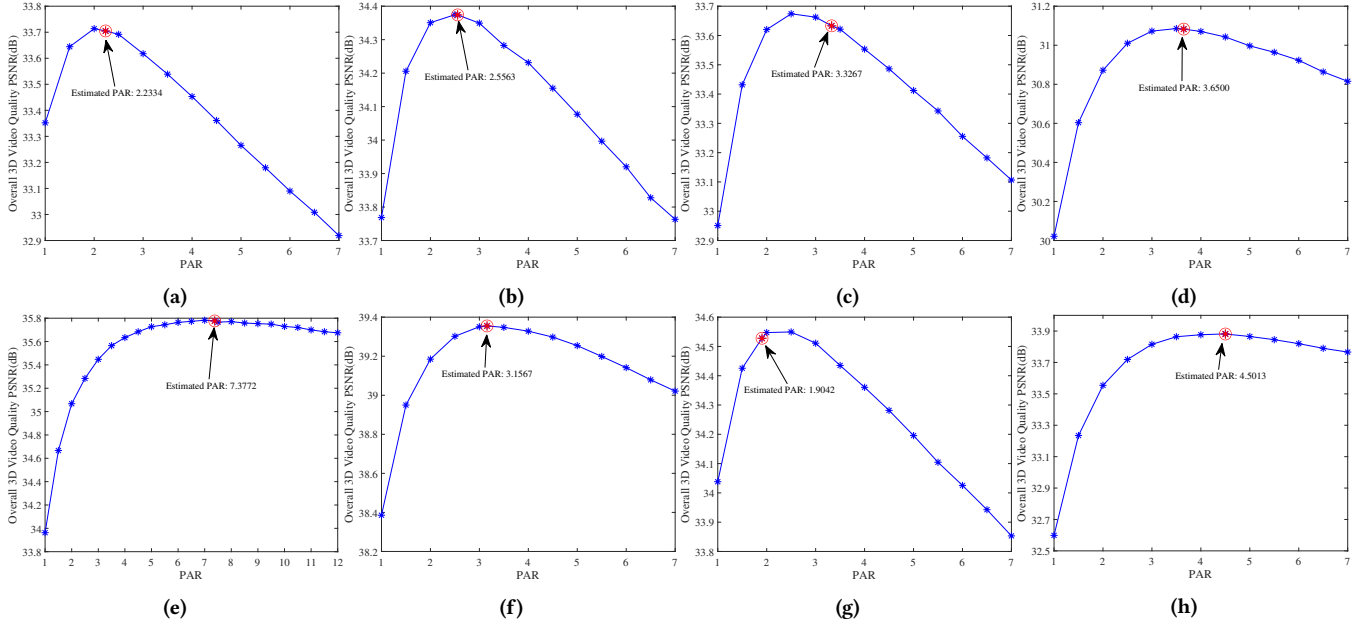
### 2.2 Problem solution

To solve the joint power and bandwidth allocation problem optimally with low complexity, we attempt to formulate a closed form for the power-distortion relationship. Suppose the total available bandwidth is  $T$  chunks, the total number of chunks of texture or depth is  $N$  (that means  $2N$  chunks for all data in a single reference view, including texture and depth),  $K$  is the bandwidth of texture to be transmitted, and  $(T - K)$  is the bandwidth of depth to be transmitted. The optimal scaling factor for sending  $K$  texture chunks is

$$g_i^t = (\lambda_i^t)^{-1/4} \sqrt{\frac{P_t}{Z \sum_{j=1}^K \sqrt{\lambda_j^t}}} \quad (4)$$

**Table 1: 3DV test sequences**

Sequences	Reference Viewpoints	Synthesized Viewpoints	Resolution	Chunk (Width x Height)	GOP
Balloons	1 and 5	2, 3, 4	1024x768	64x48	8
Kendo	1 and 5	2, 3, 4	1024x768	64x48	8
Newspaper	2 and 4	2.5, 3, 3.5	1024x768	64x48	8
Dancer	1 and 5	2, 3, 4	1920x1088	48x68	8
gtFly	1 and 5	2, 3, 4	1920x1088	48x68	8
PoznanHall2	5 and 7	5.5, 6, 6.5	1920x1088	48x68	8
PoznanStreet	3 and 5	3.5, 4, 4.5	1920x1088	48x68	8
Shark	1 and 5	2, 3, 4	1920x1088	48x68	8

**Figure 1: Different power allocation ratio performance when the CSNR is 4dB. (a) Balloons; (b) Kendo; (c) Newspaper; (d) Dancer; (e) gtFly; (f) Poznanhall2; (g) Poznanstreet; (h) Shark.****Table 2: Related Simulation Parameters**

Sequences	Estimated PAR	Full Search Method PAR
Balloons	2.23	2.05
Kendo	2.56	2.60
Newspaper	3.32	2.85
Dancer	3.65	3.65
gtFly	7.38	7.00
PoznanHall2	3.16	3.45
PoznanStreet	1.90	2.25
Shark	4.50	4.25

And the optimal scaling factor for sending  $(T - K)$  depth chunks is

$$g_i^d = (\lambda_i^d)^{-1/4} \sqrt{\frac{P_d}{Z \sum_{j=1}^{T-K} \sqrt{\lambda_j^d}}} \quad (5)$$

where  $\lambda$  is the entropy of each chunk,  $i$  and  $j$  refer to the  $j^{th}$  chunk of the  $i^{th}$  reference viewpoint and  $Z$  is the chunk size. Then, the distortion of texture and depth by sending  $K$  texture chunks and  $(T - K)$  depth chunks are

$$D_{t,i} = \frac{Z^2 \sigma_n^2}{P_t} \left( \sum_{i=1}^K \sqrt{\lambda_{j,i}^t} \right)^2 \quad (6)$$

$$D_{d,i} = \frac{Z^2 \sigma_n^2}{P_d} \left( \sum_{i=1}^{T-K} \sqrt{\lambda_{j,i}^d} \right)^2 \quad (7)$$

Based on the derivation mentioned in [5], it is clear that synthesis distortion consists of a linear combination of approximated texture and depth distortion. Thus, the  $i^{th}$  virtual viewpoint synthesis distortion could be modeled as follows:

$$D_{v,i} = \alpha_i \bar{D}_t + \beta_i \bar{D}_d + c_i \quad (8)$$

where  $\alpha_i$ ,  $\beta_i$ , and  $c_i$  represent the model parameters.  $\bar{D}_t$  and  $\bar{D}_d$  are approximated from reference viewpoint transmission under different  $PAR$  settings and noise levels. By substituting the distortion model 8, and the transmission distortions  $D_{t,i}$  and  $D_{d,i}$  into 3 the constrained optimization problem will take the following form

$$\begin{cases} D_{total}(P_t, P_d) = \arg \min_{(P_t, P_d)} \frac{Z^2 \sigma_n^2 \sum_{m=1}^M (\sum_{j=1}^K \sqrt{\lambda_{m,j}^t})^2}{M P_t} (M + \sum_{i=1}^L \alpha_i) \\ \quad + \frac{Z^2 \sigma_n^2 \sum_{m=1}^M (\sum_{j=1}^{T-K} \sqrt{\lambda_{m,j}^d})^2}{M P_d} (\sum_{i=1}^L \beta_i) + \sum_{i=1}^L c_i \\ \text{s.t. } (P_t + P_d) < P_{total}/M \end{cases} \quad (9)$$

It is easy to check the objective function convexity as  $\frac{\partial^2 D_{total}}{\partial P_t^2} > 0$ ,  $P_t > 0$  and  $\frac{\partial^2 D_{total}}{\partial P_d^2} > 0$ ,  $P_d > 0$  and therefore, the Lagrangian Multiplier method can solve the constrained optimization problem 9 by mapping it to an unconstrained optimization problem as

$$\begin{aligned} \min_{(P_t, P_d)} J = & \frac{(M + \sum_{i=1}^L \alpha_i) Z^2 \sigma_n^2 \sum_{m=1}^M (\sum_{j=1}^K \sqrt{\lambda_{m,j}^t})^2}{M P_t} + \\ & \frac{(\sum_{i=1}^L \beta_i) Z^2 \sigma_n^2 \sum_{m=1}^M (\sum_{j=1}^{T-K} \sqrt{\lambda_{m,j}^d})^2}{M P_d} + \\ & \sum_{i=1}^L c_i + \mu (P_t + P_d - P_{total}/M) \end{aligned}$$

Then, by solving the following set of equations, we get the optimal values  $P_t$  and  $P_d$ .

$$\begin{cases} \frac{\partial J}{\partial P_t} = \frac{(M + \sum_{i=1}^L \alpha_i) Z^2 \sigma_n^2 \sum_{m=1}^M (\sum_{j=1}^K \sqrt{\lambda_{m,j}^t})^2 P_t^{-2}}{M} + \mu = 0 \\ \frac{\partial J}{\partial P_d} = \frac{(\sum_{i=1}^L \beta_i) Z^2 \sigma_n^2 \sum_{m=1}^M (\sum_{j=1}^{T-K} \sqrt{\lambda_{m,j}^d})^2 P_d^{-2}}{M} + \mu = 0 \\ \frac{\partial J}{\partial \mu} = P_t + P_d - P_{total}/M = 0 \end{cases} \quad (10)$$

To consider joint texture/depth power allocation, we assume exploitation of all texture and depth chunks. Thereby, the optimal  $PAR$  between texture and depth  $PAR = \frac{P_t}{P_d}$  can be derived as

$$PAR = \frac{\sqrt{M + \sum_{i=1}^L \alpha_i} \sqrt{\sum_{m=1}^M (\sum_{j=1}^K \sqrt{\lambda_{m,j}^t})^2}}{\sqrt{\sum_{i=1}^L \beta_i} \sqrt{\sum_{m=1}^M (\sum_{j=1}^{T-K} \sqrt{\lambda_{m,j}^d})^2}} \quad (11)$$

Meanwhile, for the joint texture/depth bandwidth allocation, for  $K$  texture chunks,  $PAR_K$  between texture and depth is

$$PAR_K = \frac{\sqrt{M + \sum_{i=1}^L \alpha_i} \sqrt{\sum_{m=1}^M (\sum_{j=1}^K \sqrt{\lambda_{m,j}^t})^2}}{\sqrt{\sum_{i=1}^L \beta_i} \sqrt{\sum_{m=1}^M (\sum_{j=1}^{T-K} \sqrt{\lambda_{m,j}^d})^2}} \quad (12)$$

## 2.3 Parameters Calculation

For the joint texture/depth bandwidth allocation, an iterative search-based algorithm is designed to find the optimal value  $K_{opt}^T$ , as presented in Algorithm 1. Given the constrained bandwidth, the optimal solution obtained assuming total bandwidth is used as an upper bound to an iterative process that searches for the optimal balance between the number of chunks for texture and depth. The algorithm calculates all possible joint power allocation ratios  $PAR_K$  via changing the  $K$  and  $(T - K)$  between texture and depth frames, then searches for the optimal balance that can achieve a  $PAR$  close to the estimated  $PAR$  with no bandwidth constraints. In algorithm 1, after computing the initial energy distribution of the texture and depth chunks in each GOP, the iteration starts by considering  $K = 1$  texture chunk against  $(T - K)$  depth chunks, which means  $P_t < P_d$ . The iteration continues till the power allocation ratio  $PAR_K$  of the designated balance/combination is greater than  $PAR$ .

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### Algorithm 1: Bandwidth Allocation Algorithm

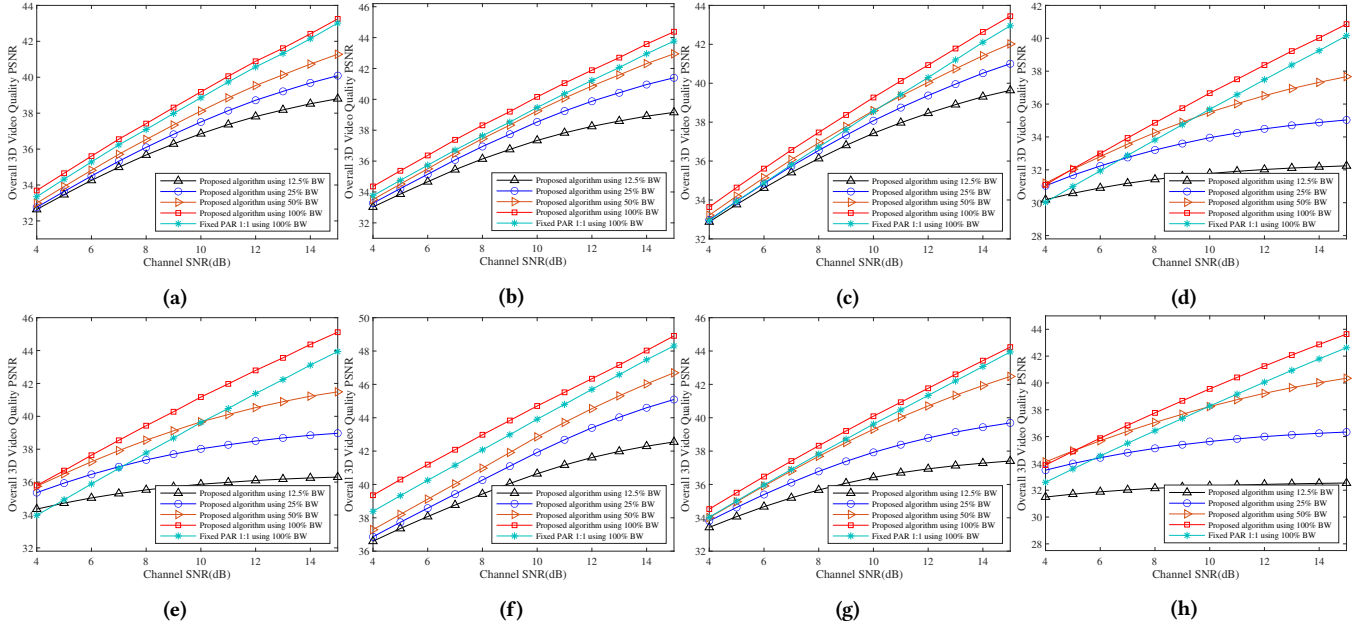
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**Input :**  $N, M, \alpha, \beta, PAR, \text{Video Sequences}$   
**Output :**  $K_{opt}^T, \lambda_{m,j}^t, \lambda_{m,j}^d$

```

1 for each sequence do
2   initialization:  $\lambda_{m,j}^t = 0, \lambda_{m,j}^d = 0$ 
3   for  $m = 1$  to  $M$  do
4     for  $j = 1$  to  $N$  do
5       Calculate  $\lambda_{m,j}^t$  and  $\lambda_{m,j}^d$  through the SoftCast
        Transmission ;
6     end
7   end
8   for  $K = 1$  to  $T - 1$  do
9     for  $m = 1$  to  $M$  do
10      for  $j = 1$  to  $K$  do
11         $\sum_m \left( \sum_j \sqrt{\lambda_{m,j}^t} \right)^2$ 
12      end
13    end
14    for  $m = 1$  to  $M$  do
15      for  $j = 1$  to  $T - K$  do
16         $\sum_m \left( \sum_j \sqrt{\lambda_{m,j}^d} \right)^2$ 
17      end
18    end
19    Calculate  $PAR_K$  according to 12;
20    if  $PAR_K > PAR$  then
21       $K_{opt}^T = K$ ;
22      break;
23    end
24  end
25 end
```

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**Figure 2: Performance comparison between Proposed power and bandwidth allocation and Fixed PAR 1:1. (a) Balloons; (b) Kendo; (c) Newspaper; (d) Dancer; (e) gtFly; (f) Poznanhall2; (g) Poznanstreet; (h) Shark.**

### 3 SIMULATION RESULTS

We conducted several simulations to assess the performance of the proposed joint power and bandwidth allocation for 3D video SoftCast.

**Test Sequence:** different standard reference 3D video sequences which belong to two different resolutions are employed in the simulation. Table 1 lists the tested sequences and their configurations.

**Wireless Simulation Environment:** we implement Matlab simulation for these experiments and adopt OFDM physical layer with settings that match 802.11.a/g standard. The results are evaluated under AWGN channels.

#### 3.1 Performance Evaluation of Joint Power Allocation

The performance of *PAR* estimation with the joint power allocation method is evaluated under the channel SNR of 4dB, considering the average PSNR of all possible display views (reference and virtual views) as the overall 3D video quality. The performance is compared to 14 *PAR* settings (*PAR* 1:1 to *PAR* 7:1, and extended to *PAR* 12:1 for gtFly sequence). As figure 1 shows, each sequence has an estimated *PAR* that differs from the other sequences, close to the global optimal *PAR*, where the global optimum leads to the best tradeoff between the reference and virtual views quality. Based on the behavior of the performance curves, it is possible to narrow the global optimal *PAR* search range, as mentioned in Table 2. A full search is conducted iteratively to reach the global optimal *PAR* with the search step set to 0.05. Figure 2 depicts the performance of the proposed joint power allocation compared to fixed *PAR* 1:1. The channel range of the evaluation extends from 4dB to 15dB. The proposed method's performance exceeds fixed *PAR* 1:1 over all

the different test sequences, and it can reach 1.8dB gain for gtFly sequence.

#### 3.2 Performance Evaluation of Joint Bandwidth Allocation

The proposed joint bandwidth allocation's performance is also illustrated in figure 2. The performance is evaluated under several bandwidth constraints (12.5%, 25%, and 50% of the total bandwidth). Note that the proposed bandwidth allocation assumes joint power allocation to distribute power between texture and depth. It can be deduced that there is a gap between sending many and a few chunks under low channel conditions based on the bandwidth constraints. As the channel SNR improves, the gap grows gradually. Transmitting fewer chunks can lead to non-negligible severe errors, which reduce the overall 3DV quality.

As the proposed *PAR* gets closer to the global optimal *PAR*, the accuracy of the proposed bandwidth allocation method improves, promoting the transmission performance under a given bandwidth allocation. Thus, for large-size test sequences divided into many chunks, we tend to consider eight frames of each sequence to calculate the model parameters instead of a single frame to assure better results.

### 4 CONCLUSION

In this work, we proposed a joint power and bandwidth allocation method for 3DV SoftCast. A power-distortion optimization problem was designed to estimate the optimal joint texture/depth *PAR*. After formulating and transforming the problem into an unconstrained optimization problem, we used the Lagrangian multiplier to solve the problem. An iterative algorithm was designed to search

for a suitable combination of texture and depth map chunks to address bandwidth resources constraint conditions. The simulation results enumerate our method's effectiveness with a gain of 1.8dB compared to the fixed *PAR* 1:1. Further, the proposed bandwidth allocation achieves a graceful overall 3DV quality over a wide range of wireless channel noise under bandwidth-constrained resources. Future work will optimize the decorrelation process to take advantage of the inter-view correlation, maximizing the transmission efficiency of 3DV SoftCast.

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